

# Peng's Maximum Principle for Stochastic Partial Differential Equations

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joint work with Wilhelm Stannat

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# Example

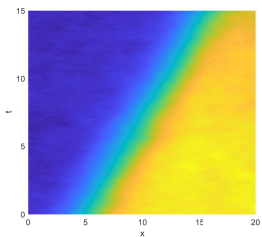
Consider stochastic Nagumo equation

$$dx_t^u = [\Delta x_t^u + x_t^u(x_t^u - 1)(a - x_t^u) + u_t] dt + \sigma dW_t, \quad x_0^u = x \in L^2(\Lambda).$$

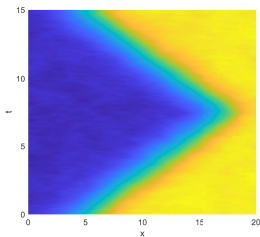
Introduce control  $u : [0, T] \times \Lambda \rightarrow \mathbb{R}$ . Minimize

$$J(u) = \mathbb{E} \left[ \int_0^T \int_{\Lambda} (x_t^u(\lambda) - x_{\bar{\lambda}}(t, \lambda))^2 d\lambda dt + \int_{\Lambda} (x_T^u(\lambda) - x^T(\lambda))^2 d\lambda \right]$$

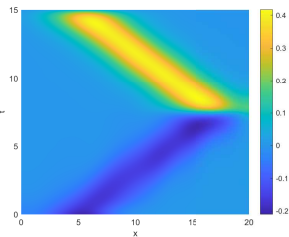
for given reference profiles  $x_{\bar{\lambda}}, x^T$ .



Uncontrolled Solution



Controlled Solution



Optimal Control

# Setting

Minimize

$$J(u) := \mathbb{E} \left[ \int_0^T \int_{\Lambda} l(x_t^u(\lambda), u_t) d\lambda dt + \int_{\Lambda} h(x_T^u(\lambda)) d\lambda \right]$$

subject to

$$\begin{cases} dx_t^u = [\Delta x_t^u + b(x_t^u, u_t)] dt + \sigma(x_t^u, u_t) dW_t, & t \in [0, T] \\ x_0^u = x \in L^2(\Lambda), \end{cases}$$

where

- $l, h$  Nemytskii operators of (at most) quadratic growth;
- $b, \sigma$  Nemytskii operators, Lipschitz;
- $(W_t)_{t \geq 0}$  cylindrical Wiener process;
- $\Lambda \subset \mathbb{R}$  bounded interval.

Goal: Derive necessary optimality condition.

# Setting

Minimize

$$J(u) := \mathbb{E} \left[ \int_0^T \int_{\Lambda} l(x_t^u(\lambda), u_t) d\lambda dt + \int_{\Lambda} h(x_T^u(\lambda)) d\lambda \right]$$

subject to

$$\begin{cases} dx_t^u = [\Delta x_t^u + b(x_t^u, u_t)] dt + \sigma(x_t^u, u_t) dW_t, & t \in [0, T] \\ x_0^u = x \in L^2(\Lambda). \end{cases}$$

- Pontryagin's maximum principle (1956): Necessary optimality condition for controlled ODEs.
- Peng's maximum principle (1990): Generalization to controlled SDEs.
- Since then: Generalizations to controlled SPDEs by Du, Fuhrman, Frankowska, Guatteri, Hu, Li, Lü, Meng, Tang, Tessitore, Zhang, . . . .  
Previous results require strong assumptions on coefficients  $l$  and  $h$  excluding quadratic costs.

# Spike Variation

Let  $\bar{u}$  be optimal. Fix  $\tau \in [0, T)$ ,  $\varepsilon > 0$ ,  $v \in U$ , and set

$$u_t^\varepsilon := \begin{cases} v, & \tau \leq t \leq \tau + \varepsilon, \\ \bar{u}_t & \text{otherwise.} \end{cases}$$

Then

$$0 \leq J(u^\varepsilon) - J(\bar{u}) = \mathbb{E} \left[ \int_0^T \int_\Lambda l(x_t^\varepsilon, u_t^\varepsilon) - l(\bar{x}_t, \bar{u}_t) d\lambda dt + \int_\Lambda h(x_T^\varepsilon) - h(\bar{x}_T) d\lambda \right].$$

- Roadmap: 1) Taylor expand integrands;  
2) Divide by  $\varepsilon$ , send  $\varepsilon \rightarrow 0$ ;  
3) Identify remaining terms.

Because of stochastic calculus, we have to Taylor expand up to second order.

# Quadratic Terms

Taylor expanding the cost functional to second order leads to the quadratic terms

$$\mathbb{E} \left[ \int_0^T \int_{\Lambda} l_{xx}(\bar{x}_t(\lambda), \bar{u}_t) y_t^\varepsilon(\lambda) y_t^\varepsilon(\lambda) d\lambda dt + \int_{\Lambda} h_{xx}(\bar{x}_T(\lambda)) y_T^\varepsilon(\lambda) y_T^\varepsilon(\lambda) d\lambda \right].$$

Peng's idea: Linearize using tensor product. Infinite-dimensional analogue:

$$H \otimes H \cong L_2(H).$$

Problem: Quadratic costs require duality analysis between  $L_1(H)$  and  $L(H)$ .

Instead, we use explicit representation

$$L^2(\Lambda) \otimes L^2(\Lambda) \cong L^2(\Lambda^2).$$

# Second Order Adjoint Equation

## Theorem (Stannat, W., SICON 2021)

*The equation*

$$\left\{ \begin{array}{l} dP_t(\lambda, \mu) = -[\Delta P_t(\lambda, \mu) + (b_x(\bar{x}_t(\lambda), \bar{u}_t) + b_x(\bar{x}_t(\mu), \bar{u}_t))P_t(\lambda, \mu) \\ \quad + \langle \sigma_x(\bar{x}_t(\lambda), \bar{u}_t), \sigma_x(\bar{x}_t(\mu), \bar{u}_t) \rangle_{L_2(\Xi, \mathbb{R})} P_t(\lambda, \mu) \\ \quad + \langle \sigma_x(\bar{x}_t(\lambda), \bar{u}_t) + \sigma_x(\bar{x}_t(\mu), \bar{u}_t), Q_t(\lambda, \mu) \rangle_{L_2(\Xi, \mathbb{R})} \\ \quad + \delta^*(l_{xx}(\bar{x}_t(\lambda), \bar{u}_t)) + \delta^*(b_{xx}(\bar{x}_t(\lambda), \bar{u}_t)p_t(\lambda)) \\ \quad + \delta^*(\langle \sigma_{xx}(\bar{x}_t(\lambda), \bar{u}_t), q_t \rangle_{L_2(\Xi, \mathbb{R})})] dt + Q_t(\lambda, \mu) dW_t \\ P_T(\lambda, \mu) = \delta^*(h_{xx}(\bar{x}_T(\lambda))) \end{array} \right.$$

*has a unique adapted solution  $(P, Q)$ , where*

$$P \in L^2([0, T] \times \Omega; L^2(\Lambda^2)) \cap L^2(\Omega; C([0, T]; H^{-1}(\Lambda^2))),$$

*and*

$$Q \in L^2([0, T] \times \Omega; L_2(\Xi; H^{-1}(\Lambda^2))).$$

## Theorem (Stannat, W., SICON 2021)

Let  $(\bar{x}, \bar{u})$  be an optimal pair. Then there exist adapted processes

$$(p, q) \in L^2([0, T] \times \Omega; H_0^1(\Lambda)) \times L^2([0, T] \times \Omega; L_2(\Xi, L^2(\Lambda)))$$

satisfying the first order adjoint equation and adapted processes

$$(P, Q) \in L^2([0, T] \times \Omega; L^2(\Lambda^2)) \times L^2([0, T] \times \Omega; L_2(\Xi, H^{-1}(\Lambda^2)))$$

satisfying the second order adjoint equation such that

$$\inf_{u \in U} \mathcal{G}(t, \bar{x}_t, u) = \mathcal{G}(t, \bar{x}_t, \bar{u}_t),$$

for almost all  $(t, \omega) \in [0, T] \times \Omega$ , where  $\mathcal{G} : [0, T] \times L^2(\Lambda) \times U \rightarrow \mathbb{R}$

$$\begin{aligned} \mathcal{G}(t, x, u) := & \int_{\Lambda} l(x(\lambda), u) d\lambda + \langle p_t, b(x, u) \rangle_{L^2(\Lambda)} + \text{tr}(\sigma(x, u)^* q_t) \\ & + \frac{1}{2} \text{tr}(\sigma(x, u)^* P_t \sigma(x, u)) - \text{tr}(\sigma(x, u)^* P_t \sigma(\bar{x}_t, \bar{u}_t)). \end{aligned}$$





W. Stannat, L. Wessels

Peng's maximum principle for stochastic partial differential equations  
*SIAM J. Control Optim.* 59 (2021), pp. 3552–3573.



W. Stannat, L. Wessels

Necessary and sufficient conditions for optimal control of semilinear SPDEs  
Submitted, [arXiv:2112.09639](https://arxiv.org/abs/2112.09639).



W. Stannat, L. Wessels

Deterministic control of stochastic reaction-diffusion equations  
*Evol. Equ. Control Theory* 10 (2021), pp. 701–722.



L. Wessels

Optimal control of stochastic reaction-diffusion equations  
Ph.D. Thesis, TU Berlin, 2022 <http://dx.doi.org/10.14279/depositonce-16218>.